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A Comparative Analysis of Multi-Criteria Decision Methods for Personnel Selection: A Practical Approach

Pablo A. Pinto-DelaCadena [1,2], Vicente Liern [2] and Andrea Vinueza-Cabezas [3,*]

[1] Business School, Universidad Internacional del Ecuador, UIDE, Quito 170411, Ecuador; papintode@uide.edu.ec
[2] Departament Matamàtiques per a l'Economia i l'Empresa, Universitat de València, 46022 Valencia, Spain; vicente.liern@uv.es
[3] Grupo de Investigación Bienestar, Salud y Sociedad, Escuela de Psicología y Educación, Universidad de Las Américas, Quito 170125, Ecuador
* Correspondence: andrea.vinueza@udla.edu.ec; Tel.: +593-23981000

Abstract: This research focused on decision-making supported by multi-criteria decision methods, specifically TOPSIS, OWA, and their respective variants within personnel selection. The study presented models aimed at facilitating the selection of the best candidate for a job through competency-based assessments and comparing the application of four methods across various scenarios. We employed methods such as TOPSIS, OWA, and two variations (Canós–Liern method and an OWA model based on mathematically replicating expert opinion). Each model provided distinct rankings and demonstrated adaptability to specific situations within a company. Furthermore, it was emphasized that each method could and should be tailored according to the company's reality to derive maximum benefit from its implementation. A crucial aspect of securing the best candidates involves understanding the context and identifying the appropriate methodology.

Keywords: TOPSIS; OWA; human resources; personnel selection; multi-criteria decision making

MSC: 62C99; 78M50

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1. Introduction

Companies operate in a turbulent environment of constant change and increasingly global competition. HR professionals are challenged to design and implement human resources practices to address these business environmental threats [1,2]. Human resource management (HRM) is a fundamental activity in companies because it is responsible for making all management decisions that affect the relationship between employees and the organization—to succeed in organizational performance [3,4].

The recruitment and selection process involves attracting and placing the right person in the appropriate position [5]. In addition, as Xiao and Björkman [6] pointed out, careful selection procedures are essential in recruitment. The selection process includes information gathered from various tools (e.g., interviews, tests, work samples) to evaluate candidates for the position, thus creating numerous barriers for applicants, and may result in choosing people who have superior abilities and behavioral scripts [7]. Furthermore, it is specified that this process should be based on candidate competencies rather than experience and academic qualifications, and interviews should focus on interpersonal skills and attitudes to ensure a cultural fit [8]. This process is not just about filling vacancies but about having the right people from the start to gain benefits through people who will contribute their efforts and skills to ensure the organization achieves its goals. Therefore, a careful selection that seeks the organization's similarity of individual and cultural values will enhance the work environment where cooperative behaviors emerge more efficiently [9].

One of the most important contributions made by Pfeffer and Veiga [10] specifies that several key elements are required:

(a) The organization must have a broad pool of candidates for selection. The more options there are, the greater the chances of finding the right candidate. This broad base of candidates provides a solid foundation for the selection process.
(b) A precise understanding of the critical skills and attributes for the position is necessary. Interview questions addressing specific cases related to these skills are crucial for accurately assessing the candidate's competencies.
(c) The skills and capabilities sought for jobs should be carefully aligned with the specific requirements of the job and the organization's strategy in its market. This alignment ensures that the candidates selected are in sync with the organization's objectives and values.
(d) A selection process focusing on finding candidates with a solid cultural fit is more likely to succeed.

Therefore, careful selection processes, i.e., strategically designed and focused on the right attributes of people, can positively impact the organization by ensuring that the right people fill the correct positions from the start [11]. Therefore, selecting the right candidate for the right job becomes more sophisticated as internal organizational changes directly impact HR selection methods [12].

Several decision methods for personnel selection processes have been found in the literature review. Among them, we have the fuzzy multi-criteria decision-making (MCDM) method [13], the ordered weighted average operator (OWAS), and the fuzzy multi-criteria decision-making methodology (TOPSIS) [14], among others. This study did not address multi-objective optimization techniques that could be explored and adapted to multi-criteria decision-making. Moreover, these techniques can be enriched with deep learning [15], collaborative neural networks [16], and other data science methods. However, we did not want to present an exhaustive list of techniques, but only those we have tested with companies that have worked well.

In previous studies, various methods have been applied to personnel selection. A concrete example comes from a study in Greece, where the fuzzy multi-criteria decision-making methodology, TOPSIS, was used to select employees for a bank. In this context, it was found that it is crucial to consider specific criteria, the weighting of these criteria, and the distances to both the ideal and the anti-ideal solution to identify the most suitable candidate [12]. Another study in Iran addressed the shortage of experienced personnel for the project manager position in the railway industry. A competency-based selection method using multigene genetic programming regression (CSPR) was implemented. The results were satisfactory, reducing the time and costs associated with implementing the project [17].

Similarly, a study in India compared two advanced methods (AHP-LP and TOPSIS-LP) for selecting supply chain employees. Both are effective, but TOPSIS is more accessible to implement, ranking applicants only once. AHP involves pairwise comparisons and is more reliable, considering consistency. The integrated approach minimizes costs by suggesting relevant positions to form an efficient team [18]. Another study examines using the ordered weighted average operator (OWA) in human resource selection in sports management. Various business decision-making techniques are applied, focusing on the OWA distance operator (OWAD), the OWA adequacy ratio (OWAAC), and the OWA index of maximum and minimum level (OWAIMAM). As a result, they found that, depending on the particular type of index used, the results may be different and lead to different decisions [19]. Likewise, a study developed the Canós–Liern method based on the definition of an ideal candidate. The aggregate fuzzy ratings of each candidate are obtained considering the individual ratings provided by the experts and then ranked according to their similarity to the ideal candidate [20]. In previous studies, there is a notable absence of research that compares the utilization of various methods, such as those chosen in this investigation, to assess diverse scenarios for ranking candidates in a selection process.

In the field of HRM, the utilization of mathematical methods to underpin decision-making is increasingly prevalent. Specifically delving into examples within personnel selection, the significance of conducting a comparative study centered on four multi-criteria decision-making methods has emerged [18]. The study will delve into a meticulous analysis of the intrinsic characteristics of each method. It will explore how these particularities can be effectively tailored and applied within each business organization's unique circumstances.

In order to accomplish this, four distinct methods will be employed:

TOPSIS: This method will rank candidates based on their relative distance from an ideal and anti-ideal solution, considering evaluations and a predefined weight vector;

OWA: This approach will prioritize identifying a candidate who globally outperforms competitors without a specific focus on any single competency;

Canós–Liern: This method aims to identify the candidate that best fits a predefined ideal profile set by the company;

Expert Evaluation Replication: Using competency evaluations of a candidate group by an expert, a linear programming model will generate a weight vector replicating the expert's evaluation for a broader candidate pool.

The main objectives of this article are listed below:

- Establish a ranking of candidates in a selection process to facilitate decision-making for identifying the most suitable candidates based on multi-criteria decision techniques;
- Identify different scenarios to apply each multi-criteria decision method according to the different levels of knowledge of the required profiles according to the specific characteristics and needs of the companies;
- Displaying the validity of candidate assessments across all competencies is crucial, as it forms the basis for employing an appropriate method to arrive at a beneficial selection.

2. Materials and Methods

HRM entails a multitude of challenges, particularly regarding social dynamics and the integration of each employee into the organizational framework [21]. Moreover, companies have the potential to harness the benefits generated by employees in their job performance through socialization and integration into the organizational culture [20,22]. As a result, the strategic formulation of acquisition policies (recruitment, selection, hiring) and development strategies (training, career progression, promotions) becomes crucial.

This work will focus on the part of acquisition policies: personnel selection. This is crucial for the company's survival, aiming to achieve an optimal workforce [20,22].

To objectify and quantify human resource magnitudes, we will use some multi-criteria decision-making techniques to support decision-making and be useful for company executives.

The methods employed in this study are widely used tools, such as OWA and TOPSIS. Additionally, two additional methods will be included: one that will replicate the results of an expert evaluator through an optimization method using a quadratic optimization program and another method to classify candidates if the company has an established ideal profile [22].

The situation we aim to address with this work is as follows:

A company has n candidates $P_1, P_2, \ldots, P_n$ for $R_0 < n$ job positions. The evaluation of each candidate in m competencies $C_1, C_2, \ldots, C_m$ is available, as shown in Table 1.

Table 1. Candidates' evaluations.

Candidates	C_1	C_2	...	C_m
P_1	v_{11}	v_{12}	...	v_{1m}
P_2	v_{21}	v_{22}	...	v_{2m}
$\vdots$	$\vdots$	$\vdots$	...	$\vdots$
P_n	v_{n1}	v_{n2}	...	v_{nm}

To select the most suitable R_0 candidates, the n candidates will be ranked, and the top R_0 candidates will be chosen. In this work, we start with the evaluated competencies, meaning we must consider how and by whom they are evaluated.

To obtain an indicator capable of providing an overall assessment of each candidate based on the evaluations of their partial competencies, we will resort to two sorting options, as shown in Figure 1.

(a) Based on distances: Calculate the distance to an ideal profile using the Canós–Liern method [20,22], or determine the ratio between the distance to an anti-ideal profile and the sum of an ideal profile and an anti-ideal profile using the TOPSIS method [14].

(b) Based on aggregation operators: If the relative weight of each competency is known, we will use an ordered weighted average (OWA) with weighted means, as proposed by Filev and Yager [23] and further developed by Yager [23–25]. If the relative weights are unknown, we will first resort to an overall assessment of a subset of candidates and then apply an ordered weighted average (OWA) with weighted means, known as Expert + OWA [22].

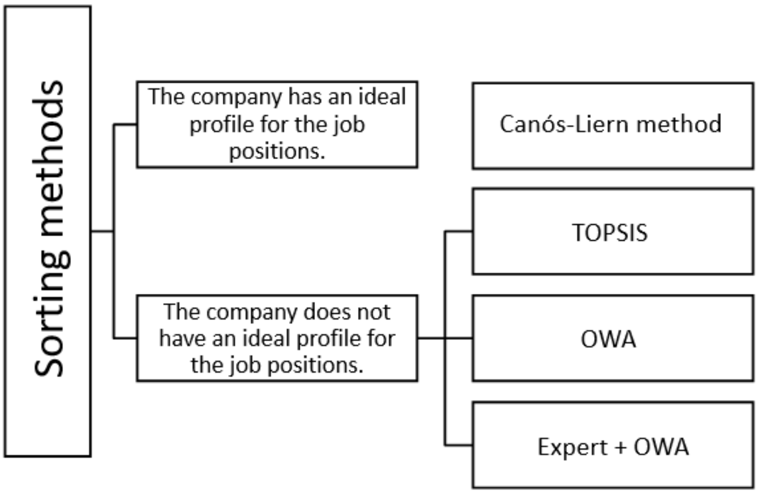

Figure 1. Sorting methods according to company reality. Source: Own elaboration.

Each case and scenario will be explained below.

Case A: The company has an ideal profile.

The company has an ideal profile for each competency and can assess candidates in these competencies. Subsequently, the candidate closest to this ideal profile will be the most suitable.

The method enables candidate selection by comparing the evaluated competencies C_1, $C_2, \ldots, C_m$ with a predefined optimal ideal profile $I = (I_1,\ I_{2,} \ldots ,\ I_m)$. Each competency is weighted using the weight vector $\boldsymbol{W} = (w_1,\ w_{2,} \ldots ,\ w_m)$, $w_j \geq 0$, $1 \leq j \leq m$, $\sum_{j=1}^{m} w_j = 1$, facilitating the selection of the candidate who best meets the company's specific requirements.

Step 1. Establishing the ideal profile for the position: Determining the value of competencies that, in line with the sought-after position, best align with the performance of duties $\boldsymbol{I} = (I_1,\ I_{2,} \ldots ,\ I_m)$. If there is a preference for one competency over others in candidate selection, a weighting of competencies based on the selector's needs will be conducted. This necessitates establishing a vector with weights $\boldsymbol{W} = (w_1,\ w_{2,} \ldots ,\ w_m)$ assigned to each evaluated competency $(C_1,\ C_{2,} \ldots ,\ C_m)$.

Step 2. Normalize the values of the data matrix: Once the competency assessments are obtained, it is necessary to normalize them. This involves dividing each term by the Euclidean norm of the column vector, as follows:

$$t_{ij} = \frac{V_{ij}}{\sqrt[2]{\sum_{1}^{n} v_{ij}^{2}}},\ 1 \leq\ i\ \leq\ n,\ 1\ \leq\ j\ \leq\ m. \tag{1}$$

where t_{ij} represents the normalized value. This will result in a new matrix with the normalized values:

$$\boldsymbol{D_1} = \begin{bmatrix} t_{11} & t_{12} & \ldots & t_{1m} \\ t_{21} & t_{22} & \ldots & t_{2m} \\ \vdots & \vdots & \ldots & \vdots \\ t_{n1} & t_{n2} & \ldots & t_{nm} \end{bmatrix} \tag{2}$$

Step 3. Introducing the weighting of evaluated competencies: Once the candidates' data have been normalized, they should be multiplied by the vector containing the weights assigned to each competency. This process allows the prioritization of one or several evaluated competencies over others.

To construct the matrix normalized by weights $\boldsymbol{D_2}$, each row of the normalized matrix is multiplied by the vector of weights $\boldsymbol{W} = (w_1,\ w_{2,}\ \ldots\ ,\ w_m)$ assigned to the m evaluated criteria, i.e., $r_{ij} = t_{ij} \times w_j$,

$$\boldsymbol{D_2} = \begin{bmatrix} r_{11} & r_{12} & \ldots & r_{1m} \\ r_{21} & r_{22} & \ldots & r_{2m} \\ \vdots & \vdots & \ldots & \vdots \\ r_{n1} & r_{n2} & \ldots & r_{nm} \end{bmatrix} \tag{3}$$

Step 4. Calculate the distance to the ideal profile: To perform this calculation, we employ the Euclidean distance of each candidate P_i to the ideal profile I.

$$\delta_i = d(P_i, I) = \frac{1}{m}\sqrt{\sum_{j=1}^{m}\left(r_{ij} - I_j\right)^2}\ ,\ 1 \leq\ \mathrm{i}\ \leq\ \mathrm{n}. \tag{4}$$

Step 5. Sort the candidates: Once this process is completed for all candidates, they should be arranged in ascending order based on distance. This allows for the selection of one or multiple candidates with the closest resemblance to the ideal profile and/or who meet the assigned weightings for each competency.

From these obtained distances $\{D_i\}_{i=1}^{n}$, we organize the candidates in the following manner.

Definition 1. *Given the candidates* $\{P_i\}_{i=1}^{n}$ *and distances* $\{D_i\}_{i=1}^{n}$*, we can state that:*

$$\begin{array}{c} P_i \text{ is better than } P_j\left(P_i \succ P_j\right) \leftrightarrow \delta_i < \delta_j \\ P_i \text{ is equivalent to } P_j\left(P_i \approx P_j\right) \leftrightarrow \delta_i = \delta_j \\ P_i \text{ is worse than } P_j\left(P_i \prec P_j\right) \leftrightarrow \delta_i > \delta_j. \end{array} \tag{5}$$

Applying Definition 1, all candidates are arranged in order, and the top-rated candidates are selected.

Case B: The company does not have an ideal profile.

This scenario occurs when the company needs a specific evaluation of the optimal profile for the position it aims to fill. It is understood that the hired candidate must meet specific requirements, but there is yet to be a previously established ideal profile. The decision in this scenario will be made using the TOPSIS method. It involves taking the best score for each competency and constructing 'ideal' and 'anti-ideal' profiles using the available data.

Each candidate is evaluated based on these created profiles, aiming to find the candidate whose scores deviate the least from the 'ideal profile' and the most from the 'anti-ideal profile' generated from the data.

The application algorithm of TOPSIS is based on evaluating a set of alternatives based on multiple criteria. It requires two fundamental elements for its application: an evaluated data set and a weight vector assigned to each of the evaluated criteria. The evaluated data matrix should contain information about each alternative and its performance relative to each evaluated criterion, and the weight vector should be used to establish the relative importance of each criterion in the evaluation [26].

Once the necessary data and weights have been established, the TOPSIS application algorithm proceeds to normalize the data matrix, identify ideal solutions for each criterion, calculate the proximity of each alternative to these solutions, and rank the alternatives based on their similarity scores. This process helps identify alternatives closest to the ideal solutions, thus aiding decision-making aligned with relevant objectives and criteria [14].

The algorithm is described below:

Step 1. Generate the decision matrix (D): This matrix contains the information of the n evaluated candidates across m criteria.

$$\boldsymbol{D} = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1m} \\ x_{21} & x_{22} & \ldots & x_{2m} \\ \vdots & \vdots & \ldots & \vdots \\ x_{n1} & x_{n2} & \ldots & x_{nm} \end{bmatrix} \tag{6}$$

Step 2. Construct the normalized matrix ($\boldsymbol{D_1}$), where each element is divided by the Euclidean norm of the column vector, i.e.,

$$t_{ij} = \frac{x_{ij}}{\sqrt[2]{\sum_1^n x_{ij}^2}}, \quad 1 \leq i \leq n,\ 1 \leq j \leq m, \tag{7}$$

and we obtain a new matrix with normalized values ($\boldsymbol{D_1}$):

$$\boldsymbol{D_1} = \begin{bmatrix} t_{11} & t_{12} & \ldots & t_{1m} \\ t_{21} & t_{22} & \ldots & t_{2m} \\ \vdots & \vdots & \ldots & \vdots \\ t_{n1} & t_{n2} & \ldots & t_{nm} \end{bmatrix} \tag{8}$$

Step 3. Construct the weighted and normalized matrix $\boldsymbol{D_2}$. By using the weight vector $\boldsymbol{W} = (w_1,\ w_{2,} \ldots,\ w_m)$ we calculate $r_{ij} = t_{ij} \times w_j$, $1 \leq i \leq n$, $1 \leq j \leq m$, i.e.,

$$\boldsymbol{D_2} = \begin{bmatrix} r_{11} & r_{12} & \ldots & r_{1m} \\ r_{21} & r_{22} & \ldots & r_{2m} \\ \vdots & \vdots & \ldots & \vdots \\ r_{n1} & r_{n2} & \ldots & r_{nm} \end{bmatrix} \tag{9}$$

Step 4. We obtain the ideal and anti-ideal solutions. In each column, we search for the maximum and minimum values. These values will be considered ideal or anti-ideal based on the criteria used for the analyzed feature. For instance, if the criterion is a feature we want to maximize, we take the maximum value in the column as the ideal solution and the minimum value as the anti-ideal solution. Conversely, if the criterion is to be minimized, we would proceed oppositely [14,27–29].

Calculate the ideal, $I = (I_1,\ I_{2,} \ldots,\ I_m)$, and the anti-ideal, $U = (U_1,\ U_{2,} \ldots,\ U_m)$, solutions:

$$I = \begin{cases} \max\limits_{1 \leq i \leq n} r_{ij}, & j \in J \\ \min\limits_{1 \leq i \leq n} r_{ij}, & j \in J\prime \end{cases} \qquad 1 \leq j \leq m, \tag{10}$$

$$U = \begin{cases} \min\limits_{1 \leq i \leq n} r_{ij}, & j \in J \\ \max\limits_{1 \leq i \leq n} r_{ij}, & j \in J\prime \end{cases} \qquad 1 \leq j \leq m, \tag{11}$$

where J is associated with "the more, the better" criteria and J' is associated with "the less, the better" criteria.

Step 5. Calculate the distance between each evaluated option and the ideal and anti-ideal solutions. For this calculation, the Euclidean distance between the weighted normalized vector Z and the ideal solution I is used, and the process is repeated to calculate the distance to the anti-ideal solution U.

$$\delta_i^+ = \sqrt[2]{\sum_{j=1}^{m}\left(r_{ij} - I_j\right)^2}, \quad \delta_i^- = \sqrt[2]{\sum_{j=1}^{m}\left(r_{ij} - U_j\right)^2}, \quad 1 \leq i \leq n. \tag{12}$$

The relative similarity of each evaluated option can be calculated as the ratio of the distance to the anti-ideal divided by the sum of the distance to the ideal and the distance to the anti-ideal [26]:

$$R_i = \frac{\delta_i^-}{\delta_i^- + \delta_i^+}, \quad 1 \leq i \leq n. \tag{13}$$

The R_i value is between 0 and 1. The value 0 indicates that the option is anti-ideal, and the value 1 indicates that it is ideal. Therefore, from the R_i value, we can order the alternatives according to the following definition:

Definition 2. *Given the evaluated alternatives* $\{P_i\}_{i=1}^{n}$ *and the relative similarities* $\{R_i\}_{i=1}^{n}$, *we can state that:*

$$\begin{gathered} P_i \text{ is better than } P_j \left(P_i \succ P_j\right) \leftrightarrow R_i > R_j, \\ P_i \text{ is equivalent to } P_j \left(P_i \approx P_j\right) \leftrightarrow R_i = R_j, \\ P_i \text{ is worse than } P_j \left(P_i \prec P_j\right) \leftrightarrow R_i < R_j. \end{gathered} \tag{14}$$

Applying Definition 2, all candidates are arranged in order, and the top-rated candidates are selected.

Case C: The company conducts a general assessment of candidates without considering the specific evaluation of any competency.

Differing from the previous two methods, here, the weights are not associated with competencies but rather with a rearrangement of these. For instance, each candidate's ratings can be sorted from highest to lowest, and based on this ranking, weights can be assigned [23]. In this scenario, two perspectives can be considered: an optimistic one, where greater weight is given to the best scores, or a pessimistic option, where less weight is given to the initial scores. Any possibility between these two options is plausible.

To formalize this, we define ordered weighted averaging (OWA) operators.

Definition 3. *An OWA operator of dimension n is a function* $O_w : R^n \to R$ *associated with a weight vector* $\boldsymbol{W} = (w_1, w_2, \ldots, w_m)$ *where* $w_i \in [0,1]$ *such that* $\sum_{i=1}^{n} w_i = 1$, *defined as:*

$$O_w(a_1, \cdots, a_n) = \sum_{i=1}^{n} w_i a_{(i)} \tag{15}$$

where $a_{(i)}$ *is the i-th largest value in* $\{a_1, a_2, \cdots, a_n\}$.

This scenario aims to find the 'best' candidate without considering the inherent ratings for each competency. Instead, these ratings will be arranged, and the assessment will be based on this order to find the ideal candidate.

Step 1. Sorting ratings obtained from candidates: Once the data have been presented, the rows should be sorted to have the best value from each candidate at the beginning of each column, regardless of which competency this value represents.

$$\boldsymbol{M} = \begin{bmatrix} x_{1(1)} & x_{1(2)} & \cdots & x_{1(m)} \\ x_{2(1)} & x_{2(2)} & \cdots & x_{2(m)} \\ \vdots & \vdots & \cdots & \vdots \\ x_{n(1)} & x_{n(2)} & \cdots & x_{n(m)} \end{bmatrix} \tag{16}$$

where $x_{\mathrm{i}(1)}$ is the best-rated competency of candidate P_i and $x_{i(m)}$ is their worst-rated competency.

Step 2. Global assessment of each candidate: The solution obtained from this model provides the weight solution vector, aiding in the assessment of all candidates using a weighted sum of the ordered features with the obtained weight vector.

$$X_i = \sum_{j=1}^{m} w_j x_{\mathrm{i(j)}} \tag{17}$$

Step 3. Sorting candidates, presenting chosen options: Once this operation is performed, finding the best global assessment among all candidates participating in this selection model is possible. It is necessary to arrange the candidates' results from highest to lowest, thereby obtaining the best-evaluated candidates.

After evaluating all candidates and all competencies with OWA, there is a collection $\{X_i\}_{i=1}^{n}$ that allows sorting candidates as follows:

Definition 4. *Given the candidates $\{P_i\}_{i=1}^{n}$ and the global assessments $\{X_i\}_{i=1}^{n}$, we can state that:*

$$\begin{array}{c} P_i \text{ is better than } P_j \left(P_i \succ P_j\right) \leftrightarrow X_i > X_j, \\ P_i \text{ is equivalent to } P_j \left(P_i \approx P_j\right) \leftrightarrow X_i = X_j \\ P_i \text{ is worse than } P_j \left(P_i \prec P_j\right) \leftrightarrow X_i < X_j. \end{array} \tag{18}$$

Applying Definition 4, all candidates are arranged in order, and the top-rated candidates are selected.

Case D: The company relies on the assessment of a certain group of experts, and based on this evaluation, an attempt is made to replicate this assessment for a larger group of individuals.

At times, when the number of candidates is high, obtaining expert and comprehensive evaluations for all of them proves to be a highly costly process, both in terms of time and finances. Hence, one option is to assess fewer candidates and attempt to 'uncover' the weights used, even if performed intuitively. Extensive literature [20,22–25,30] advocates that, for a global assessment not based on specific competency scores, the expert focuses more on what the candidate does best and worst, regardless of the competency involved.

Let us assume we have the opinion of a unique expert, E, who needs to be made aware of each candidate's competency ratings. This expert globally evaluates L candidates, denoted as $P_1, P_2, \ldots, P_L$, where $L < n$, as follows:

$$VE_k = Global\ Evaluation\ of\ P_k, \quad k = 1, \ldots, L. \tag{19}$$

Additionally, we have evaluated and ranked the competencies of these L candidates. In Table 2, the rows are ordered from highest to lowest.

Table 2. Candidates' evaluations ordered from high to low.

Candidates	C_1	C_2	...	C_m
P_1	$v1(1)$	$v1(2)$	...	$v1(m)$
P_2	$v2(1)$	$v2(2)$	...	$v2(m)$
$\vdots$	$\vdots$	$\vdots$	...	$\vdots$
P_n	$vL(1)$	$vL(2)$	...	$vL(m)$

To incorporate this idea, we will use OWA operators in three steps.

Step 1. Through a least squares problem, we approximate the weights experts use in the small sample.
Step 2. We use the obtained weights to conduct an OWA analysis with the remaining candidates.
Step 3. We rank the candidates based on their aggregated evaluations.

We obtain the weights that best fit the evaluations using the following quadratic optimization program (P).

$$(P)\ Min \sum_{j=1}^{L}\left(\sum_{j=1}^{m}\left(w_j v_{i(j)} - VE_i\right)^2\right)$$

$$Subject\ to: \sum\nolimits_{j=1}^{m} w_j = 1 \tag{20}$$

$$w_j \geq 0,\ 1 \leq j \leq m$$

The solution to (P) is the weight vector $\boldsymbol{W}^* = \left(w_1^*,\ w_2^*, \ldots,\ w_m^*\right)$. With this solution, considering the evaluations (arranged from highest to lowest in each row) of each candidate, we obtain:

$$V_i = \sum\nolimits_{j=1}^{m} w_j^* v_{\mathrm{i(j)}}. \tag{21}$$

Definition 5. *Given the candidates* $\{P_i\}_{i=1}^{n}$ *and their global evaluations* $\{V_i\}_{i=1}^{n}$*, we can state that:*

$$\begin{array}{c} P_i \text{ is better than } P_j\ \left(P_i \succ\ P_j\right) \leftrightarrow\ V_i > V_j, \\ P_i \text{ is equivalent to } P_j\ \left(P_i \approx\ P_j\right) \leftrightarrow\ V_i = V_j, \\ P_i \text{ is worse than } P_j\ \left(P_i \prec\ P_j\right) \leftrightarrow\ V_i < V_j. \end{array} \tag{22}$$

3. Results

Below are the candidate evaluations used for solving the cases in this study. The competencies (Table 3) and their ratings for 50 candidates are presented in the Appendix A (Tables A1 and A2). Table A1 displays the original data of the assessed competencies; these values will be used to solve Cases A and B. Table A2 shows each candidate's competencies arranged from highest to lowest; these values will be used to solve Cases C and D.

Table 3. Competencies.

Competence	Notation
Analytical Skills	C1
Information Transmission	C2
Task Knowledge	C3
Communication Skills	C4
Versatility	C5
Team Management	C6
Organization and Planning	C7
Adaptability to New Situations	C8
Proactivity	C9
Decision-Making Skills	C10

To present the values ordered from highest to lowest of the evaluated competencies in Table A2, please note that C(j) does not represent the j-th competency, but rather the one that, once ordered, occupies the j-th position.

In Figure 2, you can observe the necessary inputs and the formulation of the scenarios required or most suitable for utilizing each of the four proposed methods. Subsequently, you will find the development, and the results of each method applied to the problem in this study will be presented.

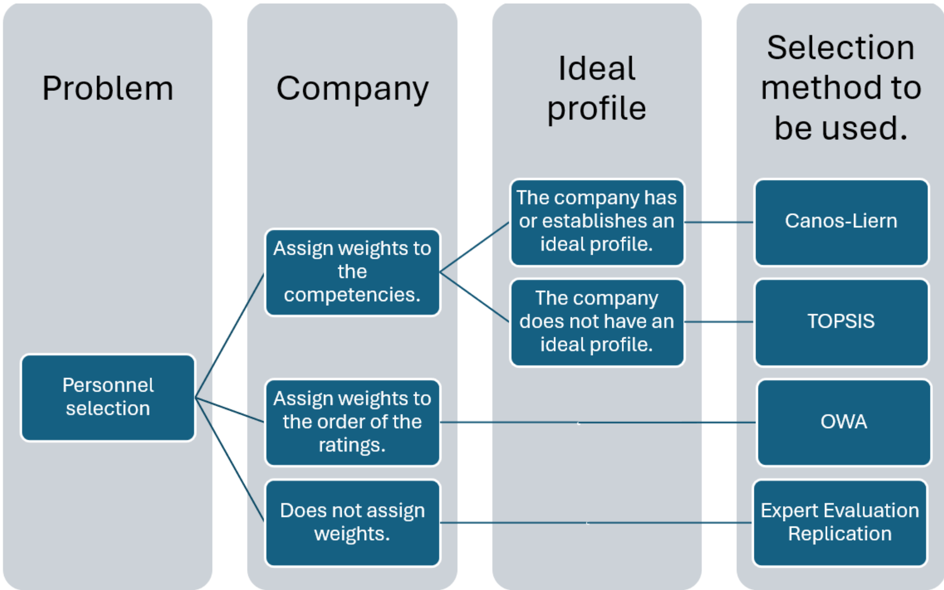

Figure 2. Scheme of the method to be used according to the company's reality. Note: In this figure, you will see the presentation of each method used in this research and the conditions for its application.

Case A:

For solving this method, we will use the parameters given in Table 4.

Table 4. Case A data.

Competence	Notation	Ideal Profile	Weight
Analytical Skills	C1	0.7	0.08
Information Transmission	C2	0.4	0.08
Task Knowledge	C3	0.9	0.08
Communication Skills	C4	0.6	0.14
Versatility	C5	0.6	0.08
Team Management	C6	1	0.15
Organization and Planning	C7	0.5	0.08
Adaptability to New Situations	C8	0.7	0.08
Proactivity	C9	0.4	0.08
Decision-Making Skills	C10	0.8	0.15

Applying Definition 1, we have the following ranking of candidates as expressed in Table 5.

Table 5. Case A results.

Case A									
Candidate	**Ranking**	**Candidate**	**Ranking**	**Candidate**	**Ranking**	**Candidate**	**Ranking**	**Candidate**	**Ranking**
$V7$	1	$V49$	11	$V31$	21	$V32$	31	$V46$	41
$V15$	2	$V6$	12	$V47$	22	$V37$	32	$V21$	42
$V12$	3	$V38$	13	$V44$	23	$V29$	33	$V42$	43
$V8$	4	$V13$	14	$V34$	24	$V50$	34	$V11$	44
$V35$	5	$V19$	15	$V27$	25	$V33$	35	$V14$	45
$V48$	6	$V43$	16	$V18$	26	$V3$	36	$V39$	46
$V23$	7	$V17$	17	$V28$	27	$V1$	37	$V36$	47
$V41$	8	$V25$	18	$V24$	28	$V20$	38	$V16$	48
$V5$	9	$V4$	19	$V10$	29	$V22$	39	$V9$	49
$V26$	10	$V40$	20	$V45$	30	$V30$	40	$V2$	50

Case B:

This time, it will be solved as an multi-criteria decision-making problem with 10 criteria (the 10 competencies studied). In this scenario, for all criteria, the aim is to maximize the value of each competency, and the weights used will be the same as in Case A.

Following the steps described in Definition 2, based on the evaluations of all candidates in all competencies, the ideal and anti-ideal solutions are presented in Table 6.

Table 6. Case B data.

Competence	Notation	Ideal Profile	Anti-Ideal	Weight
Analytical Skills	C1	0.017	0	0.08
Information Transmission	C2	0.02	0	0.08
Task Knowledge	C3	0.019	0	0.08
Communication Skills	C4	0.032	0	0.14
Versatility	C5	0.018	0	0.08
Team Management	C6	0.033	0.003	0.15
Organization and Planning	C7	0.018	0	0.08
Adaptability to New Situations	C8	0.018	0	0.08
Proactivity	C9	0.02	0	0.08
Decision-Making Skills	C10	0.033	0	0.15

The ranking of candidates is displayed in Table 7.

Table 7. Case B results.

Case B									
Candidate	**Rank**	**Candidate**	**Rank**	**Candidate**	**Rank**	**Candidate**	**Rank**	**Candidate**	**Rank**
P12	1	P23	11	P10	21	P42	31	P30	41
P7	2	P48	12	P31	22	P32	32	P22	42
P8	3	P35	13	P19	23	P37	33	P11	43
P5	4	P40	14	P25	24	P1	34	P36	44
P15	5	P17	15	P18	25	P45	35	P2	45
P26	6	P4	16	P47	26	P27	36	P14	46
P49	7	P13	17	P33	27	P29	37	P39	47
P41	8	P34	18	P28	28	P3	38	P46	48
P6	9	P43	19	P44	29	P20	39	P16	49
P38	10	P50	20	P24	30	P21	40	P9	50

Case C:

Following the steps described in Definition 4, based on the values of Table A2, the results are presented in Table 8.

Table 8. Case C results.

Case C									
Candidate	**Rank**	**Candidate**	**Rank**	**Candidate**	**Rank**	**Candidate**	**Rank**	**Candidate**	**Rank**
P12	1	P35	11	P24	21	P10	31	P31	41
P38	2	P47	12	P34	22	P27	32	P21	42
P26	3	P37	13	P40	23	P7	33	P18	43
P41	4	P19	14	P25	24	P6	34	P46	44
P5	5	P2	15	P30	25	P8	35	P20	45
P49	6	P43	16	P45	26	P50	36	P4	46
P13	7	P3	17	P17	27	P9	37	P39	47
P15	8	P29	18	P28	28	P32	38	P22	48
P48	9	P44	19	P11	29	P42	39	P16	49
P23	10	P14	20	P1	30	P33	40	P36	50

Case D:

For the resolution of this case, the global evaluation performed by an expert on 10 candidates will be considered. These evaluations are presented in Table 9:

Table 9. Expert global evaluation.

Expert's Global Evaluation									
PE1	**PE2**	**PE3**	**PE4**	**PE5**	**PE6**	**PE7**	**PE8**	**PE9**	**PE10**
0.7471	0.752	0.7712	0.798	0.8647	0.8373	0.9275	0.8549	0.6284	0.7863

Based on these evaluations, the programming model described in the case has been created.

$$\begin{array}{c}(P)\ Min\ \sum_{j=1}^{10}\left(\sum_{j=1}^{10}\left(w_j v_{i(j)} - VE_i\right)^2\right)\\ Subject\ to:\ \sum_{j=1}^{m} w_j = 1\\ w_j \geq 0,\ 1 \leq j \leq 10\end{array} \tag{23}$$

The following weights have been obtained (see Table 10), which will allow replicating the evaluation performed by the expert.

Table 10. Expert replication weights.

Expert Replication Weights.									
w(1)	**w(2)**	**w(3)**	**w(4)**	**w(5)**	**w(6)**	**w(7)**	**w(8)**	**w(9)**	**w(10)**
0.730	0.000	0.000	0.079	0.000	0.000	0.036	0.000	0.000	0.154

With these weights, as explained in Definition 5, the ranking of candidates is presented in Table 11.

Table 11. Case D results.

Case D									
Candidate	**Rank**	**Candidate**	**Rank**	**Candidate**	**Rank**	**Candidate**	**Rank**	**Candidate**	**Rank**
P7	1	P19	11	P25	21	P42	31	P40	41
P5	2	P34	12	P27	22	P45	32	P26	42
P41	3	P23	13	P17	23	P22	33	P36	43
P49	4	P44	14	P33	24	P46	34	P10	44
P6	5	P14	15	P31	25	P11	35	P9	45
P13	6	P38	16	P32	26	P39	36	P16	46
P15	7	P43	17	P50	27	P18	37	P2	47
P48	8	P12	18	P21	28	P29	38	P24	48
P4	9	P35	19	P30	29	P1	39	P20	49
P8	10	P47	20	P3	30	P37	40	P28	50

To facilitate the comparison between the rankings obtained with the four methods, we present a graph (see Figure 3) and a summary where the coincidences in ranking between the different methods are highlighted by shading the cells (see Table 12). Although exact matchings in the order are not numerous, looking at Figure 3 suffices to confirm that the rankings in this case do not have a significant difference.

For instance, Candidate 12 is very well positioned with the three methods that do not require the involvement of an external expert. However, upon their participation, this candidate drops from the top position to position number 18.

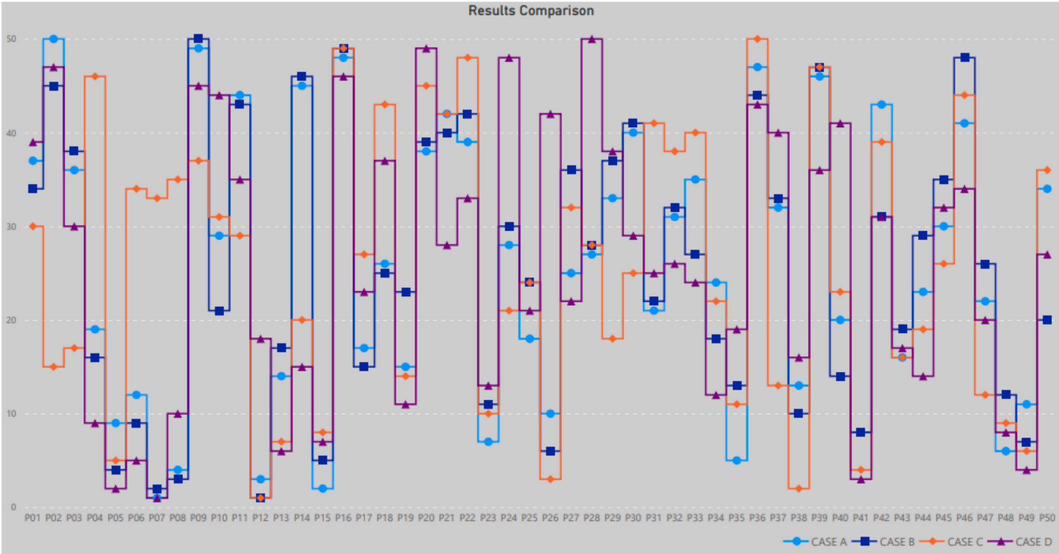

Figure 3. Comparison of results. Note: In this figure, you will see the ranking each candidate achieved using each method. Source: Own elaboration.

Table 12. Ranking comparison.

Ranking Comparison									
Ranking	**Case A**	**Case B**	**Case C**	**Case D**	**Ranking**	**Case A**	**Case B**	**Case C**	**Case D**
1	**P7**	**P12**	**P12**	**P7**	26	P18	P47	P45	P32
2	P15	P7	P38	P5	27	P28	P33	P17	P50
3	P12	P8	P26	P41	28	P24	**P28**	**P28**	P21
4	P8	P5	P41	P49	29	P10	P44	P11	P30
5	P35	P15	P5	P6	30	P45	P24	P1	P3
6	P48	P26	P49	P13	31	P32	**P42**	P10	**P42**
7	P23	P49	P13	P15	32	P37	P32	P27	P45
8	**P41**	**P41**	P15	P48	33	P29	P37	P7	P22
9	P5	P6	P48	P4	34	P50	P1	P6	P46
10	P26	P38	P23	P8	35	P33	P45	P8	P11
11	P49	P23	P35	P19	36	P3	P27	P50	P39
12	P6	P48	P47	P34	37	P1	P29	P9	P18
13	P38	P35	P37	P23	38	P20	P3	P32	P29
14	P13	P40	P19	P44	39	P22	P20	P42	P1
15	P19	P17	P2	P14	40	P30	P21	P33	P37
16	**P43**	P4	**P43**	P38	41	P46	P30	P31	P40
17	P17	P13	P3	P43	42	**P21**	P22	**P21**	P26
18	P25	P34	P29	P12	43	P42	P11	P18	P36
19	P4	P43	P44	P35	44	P11	P36	P46	P10
20	P40	P50	P14	P47	45	P14	P2	P20	P9
21	P31	P10	P24	P25	46	P39	P14	P4	P16
22	P47	P31	P34	P27	47	P36	**P39**	**P39**	P2
23	P44	P19	P40	P17	48	P16	P46	P22	P24
24	P34	P25	P25	P33	49	P9	P16	P16	P20
25	P27	P18	P30	P31	50	P2	P9	P36	P28

Note: This table shows the ranking of each method and which individual obtained that place; Candidates who obtained the same ranking in different methods are highlighted in bold.

4. Discussion

This study aims to analyze different approaches to multi-criteria decision-making concerning personnel selection. The aim is to decide on the choice of candidates, considering different levels of knowledge of the ideal profile being required. This study has analyzed and compared four scenarios to identify similarities and differences in applying each method. Specific parameters have also been defined to determine when the utilization of one method is preferable over another.

Our results demonstrate the following: In Case A, we identified the candidate who best fits the ideal profile defined by the company. The obtained order is determined by each candidate's proximity to the ideal profile. These findings align with prior research. For instance, it has been determined that when a company is acquainted with the ideal profile and weighs each assessed competency for the job position, it can establish an optimal evaluation criterion to find the best candidate. This criterion leads to selecting candidates closely aligned with the company's needs [20].

In Case B, our results are determined by evaluating the relative proximity of each candidate, calculating their distance from both the "ideal" and "anti-ideal" solutions derived from the model. This analysis not only assesses candidates' performance but also requires that competencies with lower scores are not excessively deficient. Preference is given to an outstanding candidate, even in areas where they could perform better. These findings align with prior research [12]. Classification methods like TOPSIS enable us to conduct a candidate selection that ensures finding the most suitable individuals for the available positions. Implementing this model ensures that selected candidates not only excel in their strongest competencies but also that areas with lower scores are positioned as far as possible from the "anti-ideal" solution within the model.

In the third case, Case C, candidates' ranking is based on their overall performance in evaluations, detached from specific performances in individual competencies. This approach emphasizes candidates' highest scores, as the ratings are arranged from highest to lowest for the final assessment. This model offers a solution that can be highly beneficial in specific scenarios, such as when the company does not have any preference for the competencies evaluated. Through this model, priority can be given to higher scores to seek outstanding candidates in three or four competencies or to select the candidate with the most minor deficit, focusing solely on the three or four weakest competencies and basing the decision on that outcome. This finding indicates that aggregation methods like OWA have been extensively researched in decision-making environments, and their application in personnel selection has evolved into a valuable tool for team development. This outcome parallels the satisfactory outcomes achieved by Dwivedi and Vakil Zadeh [18] in their research.

Finally, in Case D, the outcomes stem from emulating the preferences of a human resources expert, expressed within a small group of candidates, and replicated through a mathematical model. Theoretically, the results obtained using this method mirror the expert's viewpoint, suggesting that this ranking would resemble the outcome if the expert had evaluated all candidates. These findings support previous research signifying the crucial role of the economic factor in establishing a quality selection process that aligns with corporate interests [22,24]. Also, emphasizing how leveraging an expert's evaluation within a small group of candidates can be the starting point for a successful selection process [22].

The use of these methodologies can significantly aid in human resources practices. Those leading these processes must have access to or know how these mathematical models can benefit this field. Particularly, small- and medium-sized enterprises can leverage these multi-criteria decision-making techniques to ensure that their hiring decisions align with the company's objectives. Different models can be tailored to the specific needs of each company and can significantly enhance their selection processes. Additionally, these models can be extended to other areas of the company, such as promotions and compensation, among others.

This study encountered several limitations, with access to evaluated individuals' data being one of the most significant. While the 50 subjects in this study provide relevant information, having more data from the evaluated individuals could generate more robust results that support decision-making. Additionally, this study did not consider the evaluation method used for these individuals; only data collected after the evaluation were included. Furthermore, one of the inherent challenges in using multi-criteria decision methods in real personnel selection situations arises from the subjectivity associated with assigning weights to the various criteria, which is compounded by variations among different decision-makers. Determining the relative importance of each criterion thus becomes a complex process that often lacks consensus. In addition, the effective implementation of these methods requires a certain level of expertise, which implies that decision-makers must be adequately trained to understand and apply these methodologies, which can be a limitation in real-world environments.

Future research could involve implementing fuzzy logic, allowing the development of more robust and versatile multi-criteria decision-making or optimization models capable of considering a broader range of scenarios to enhance the decision-making process. It would also be pertinent to integrate these models, whether fuzzy or not, into candidate evaluations to enhance the quality of information before utilization. Expanding the use of multi-criteria decision-making to other areas of human resources will enable companies to manage their most valuable resource, their employees, more effectively.

5. Conclusions

Multi-criteria decision-making methods based on distances and aggregation operators (such as TOPSIS, OWA, and their derivatives) can significantly support personnel selection. This study confirms that some of the drawbacks attributed to applying quantitative techniques in the human resources field can be avoided by appropriately selecting the method. Specifically, we refer to the existence of ideal profiles for the positions to be filled or the necessity of prior knowledge of the relative importance of each competency. When dealing with established and experienced companies, these requirements are easy to establish. However, newly created companies, or those arising from mergers or acquisitions, often need consensus patterns.

In essence, the assessments of competencies made for various candidates can be employed in many personnel-selection scenarios. This achievement transforms multi-criteria decision-making methods into genuine decision support systems.

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Appendix A

In this appendix, in Table A1, we show the outcome of the evaluation of the 50 candidates. In Table A2, we provide the outcome of the evaluation of the 50 candidates ordered from highest to lowest.

Table A1. Candidates' results.

Candidates	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
P1	0.1	0.5	0.7	0.7	0.2	0.5	0.9	0.8	0.7	0.2
P2	0.2	0	0.1	0.7	0	0.1	0.1	0.4	0.5	0.9
P3	0.6	0	0.6	0.6	0.3	0.4	1	0.9	0.6	0.3
P4	1	0.8	0.9	1	0.2	0.3	0.4	0.4	0.4	0.6
P5	0.6	0.9	0.8	0.7	1	0.4	0.5	0.8	0.9	0.7

Table A1. *Cont.*

Candidates	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
P6	1	0.5	0.4	0.5	0.4	0.6	0.5	0.5	0.9	0.9
P7	0.8	0.9	1	0.5	0.9	0.7	0.7	0.7	0.5	0.8
P8	0.6	0.5	0.4	0.9	0.8	0.9	0.3	0.4	0.2	1
P9	0.9	0.9	0	0.2	0.4	0.3	0.2	0.6	0.1	0.4
P10	0.3	0.4	0.5	0.6	0.6	0.4	0.5	0.6	0.8	0.7
P11	0.3	0.4	0.2	0.2	0	0.9	1	0.5	0.6	0.3
P12	0	0.8	0.7	0.8	1	0.7	0.6	0.8	1	0.8
P13	1	0.7	0.9	0.8	0.6	0.5	0.6	0.7	0.4	0.3
P14	1	0.5	0.4	0.3	0.6	0.2	0.8	1	0.5	0.2
P15	0.4	0.9	1	0.5	0.4	1	0.2	0.7	0.6	0.8
P16	0.3	0.1	0	0.2	0.4	0.2	0.2	0.6	0.8	0.9
P17	0.6	0.4	0.2	0.8	0.6	1	0.8	0.1	0.3	0.5
P18	0.2	0.2	1	0.5	0	0.5	0.6	0.5	0.2	1
P19	0.9	0.3	0.8	0.2	0.9	1	0.5	0.2	0.7	0.4
P20	0.3	0.4	0.5	0	0.2	0.8	0.3	0.4	0.6	0.8
P21	0.4	0.6	0.5	0.3	1	0.3	0.4	0.1	0.2	0.8
P22	0.7	0	0.3	0.1	1	0.8	0.5	0.2	0.2	0.6
P23	0.7	0.3	0.8	0.4	0.9	0.7	0.1	0.8	0.5	1
P24	0.4	0.4	0.6	0.2	0.3	0.5	0.6	0.8	0.7	0.8
P25	1	0.3	0.6	0.4	0.5	1	0.2	0.3	0.4	0.5
P26	0.6	0.8	0.4	0.4	0.7	0.8	0.6	0.8	0.8	0.8
P27	1	0.4	0.7	0.2	0.3	1	0.9	0.3	0.1	0.3
P28	0.5	0.2	0.4	0.5	0.4	0.6	0.7	0.7	0.3	0.7
P29	0.8	0.7	0.6	0.3	0.2	0.3	0.8	0.9	0.6	0.5
P30	0.6	0.2	0.3	0.5	1	0.5	0.8	0.5	1	0
P31	0.6	0.3	0.5	0.9	0.2	1	0.1	0.7	0.2	0.3
P32	1	1	0.4	0.2	0.4	0.7	0.3	0	0.4	0.7
P33	0.8	1	0	0.9	0.2	0.8	0.5	0.3	0.3	0.2
P34	0.3	0.5	0.3	1	0.5	0.8	0.3	0.5	0.6	0.4
P35	1	0.6	0.9	0.4	1	0.8	0.2	0.4	0	0.9
P36	0.3	0.5	0.2	0.9	0.4	0.4	0	0.2	0.3	0.4
P37	0.9	0.6	0.3	0.7	0.9	0.5	0.6	0.8	0.7	0
P38	0.6	1	0.6	0.7	0.9	0.1	0.7	0.6	0.7	1
P39	0.6	0	0.3	0.3	1	0.3	0.5	0.4	0.2	0.7
P40	0	0.2	0.3	0.5	0.3	0.7	0.8	0.9	0.9	0.9
P41	1	0.2	0.8	1	0.6	0.7	1	0.4	1	0.3
P42	0.4	0.8	0	0.9	1	0.2	0.6	0.4	0.3	0.5
P43	0.8	0.2	0.9	1	0.3	0.3	0.8	1	0.1	0.5
P44	1	0.6	0.8	0.6	0.9	0.8	0.3	0.1	0.5	0.1
P45	0.4	0.3	1	0	0.3	0.3	1	0.6	0.4	1
P46	0.4	0	0.5	0.5	1	0.6	0.4	1	0.3	0
P47	0.6	1	0.8	0.6	0	0.7	0.7	1	0.8	0
P48	0.5	0.5	1	0.2	0.3	0.9	0.9	0.7	0.6	0.8
P49	1	0.4	0.3	1	0.7	0.6	1	0.8	0.4	0.5
P50	0.1	1	0.3	0.8	0	0.4	0.6	0.5	0.8	0.7

Table A2. Candidates' results ordered from high to low.

Candidates	C(1)	C(2)	C(3)	C(4)	C(5)	C(6)	C(7)	C(8)	C(9)	C(10)
P1	0.9	0.8	0.7	0.7	0.7	0.5	0.5	0.2	0.2	0.1
P2	0.9	0.7	0.5	0.4	0.2	0.1	0.1	0.1	0	0
P3	1	0.9	0.6	0.6	0.6	0.6	0.4	0.3	0.3	0
P4	1	1	0.9	0.8	0.6	0.4	0.4	0.4	0.3	0.2
P5	1	0.9	0.9	0.8	0.8	0.7	0.7	0.6	0.5	0.4

Table A2. *Cont.*

Candidates	C(1)	C(2)	C(3)	C(4)	C(5)	C(6)	C(7)	C(8)	C(9)	C(10)
P6	1	0.9	0.9	0.6	0.5	0.5	0.5	0.5	0.4	0.4
P7	1	0.9	0.9	0.8	0.8	0.7	0.7	0.7	0.5	0.5
P8	1	0.9	0.9	0.8	0.6	0.5	0.4	0.4	0.3	0.2
P9	0.9	0.9	0.6	0.4	0.4	0.3	0.2	0.2	0.1	0
P10	0.8	0.7	0.6	0.6	0.6	0.5	0.5	0.4	0.4	0.3
P11	1	0.9	0.6	0.5	0.4	0.3	0.3	0.2	0.2	0
P12	1	1	0.8	0.8	0.8	0.8	0.7	0.7	0.6	0
P13	1	0.9	0.8	0.7	0.7	0.6	0.6	0.5	0.4	0.3
P14	1	1	0.8	0.6	0.5	0.5	0.4	0.3	0.2	0.2
P15	1	1	0.9	0.8	0.7	0.6	0.5	0.4	0.4	0.2
P16	0.9	0.8	0.6	0.4	0.3	0.2	0.2	0.2	0.1	0
P17	1	0.8	0.8	0.6	0.6	0.5	0.4	0.3	0.2	0.1
P18	1	1	0.6	0.5	0.5	0.5	0.2	0.2	0.2	0
P19	1	0.9	0.9	0.8	0.7	0.5	0.4	0.3	0.2	0.2
P20	0.8	0.8	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0
P21	1	0.8	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.1
P22	1	0.8	0.7	0.6	0.5	0.3	0.2	0.2	0.1	0
P23	1	0.9	0.8	0.8	0.7	0.7	0.5	0.4	0.3	0.1
P24	0.8	0.8	0.7	0.6	0.6	0.5	0.4	0.4	0.3	0.2
P25	1	1	0.6	0.5	0.5	0.4	0.4	0.3	0.3	0.2
P26	0.8	0.8	0.8	0.8	0.8	0.7	0.6	0.6	0.4	0.4
P27	1	1	0.9	0.7	0.4	0.3	0.3	0.3	0.2	0.1
P28	0.7	0.7	0.7	0.6	0.5	0.5	0.4	0.4	0.3	0.2
P29	0.9	0.8	0.8	0.7	0.6	0.6	0.5	0.3	0.3	0.2
P30	1	1	0.8	0.6	0.5	0.5	0.5	0.3	0.2	0
P31	1	0.9	0.7	0.6	0.5	0.3	0.3	0.2	0.2	0.1
P32	1	1	0.7	0.7	0.4	0.4	0.4	0.3	0.2	0
P33	1	0.9	0.8	0.8	0.5	0.3	0.3	0.2	0.2	0
P34	1	0.8	0.6	0.5	0.5	0.5	0.4	0.3	0.3	0.3
P35	1	1	0.9	0.9	0.8	0.6	0.4	0.4	0.2	0
P36	0.9	0.5	0.4	0.4	0.4	0.3	0.3	0.2	0.2	0
P37	0.9	0.9	0.8	0.7	0.7	0.6	0.6	0.5	0.3	0
P38	1	1	0.9	0.7	0.7	0.7	0.6	0.6	0.6	0.1
P39	1	0.7	0.6	0.5	0.4	0.3	0.3	0.3	0.2	0
P40	0.9	0.9	0.9	0.8	0.7	0.5	0.3	0.3	0.2	0
P41	1	1	1	1	0.8	0.7	0.6	0.4	0.3	0.2
P42	1	0.9	0.8	0.6	0.5	0.4	0.4	0.3	0.2	0
P43	1	1	0.9	0.8	0.8	0.5	0.3	0.3	0.2	0.1
P44	1	0.9	0.8	0.8	0.6	0.6	0.5	0.3	0.1	0.1
P45	1	1	1	0.6	0.4	0.4	0.3	0.3	0.3	0
P46	1	1	0.6	0.5	0.5	0.4	0.4	0.3	0	0
P47	1	1	0.8	0.8	0.7	0.7	0.6	0.6	0	0
P48	1	0.9	0.9	0.8	0.7	0.6	0.5	0.5	0.3	0.2
P49	1	1	1	0.8	0.7	0.6	0.5	0.4	0.4	0.3
P50	1	0.8	0.8	0.7	0.6	0.5	0.4	0.3	0.1	0

References

1. Ferguson-Amores, M.G.; García-Rodríguez, M.; Ruiz-Navarro, J. Strategies of Renewal the Transition from "Total Quality Management" to the "Learning Organization". *Manag. Learn.* **2005**, *36*, 149–180. [CrossRef]
2. Kim, D.H. *The Link between Individual and Organizational Learning*; Butterworth-Heinemann: Oxford, UK, 2009; ISBN 9780080517926.
3. Boxall, P.; Macky, K. High Performance Work Systems and Organisational Performance: Bridging Theory and Practice. *Asia Pac. J. Hum. Resour.* **2007**, *45*, 261–270.
4. Seeck, H.; Diehl, M.R. A Literature Review on HRM and Innovation–Taking Stock and Future Directions. *Int. J. Hum. Resour. Manag.* **2017**, *28*, 913–944. [CrossRef]
5. Huselid, M. The Impact of Human Resource Management Practices on Turnover, Productivity, and Corporate Financial Performance. *Acad. Manag. J.* **1995**, *38*, 635–872. [CrossRef]

6. Xiao, Z.; Björkman, I. High Commitment Work Systems in Chinese Organizations: A Preliminary Measure Este Es. *Manag. Organ. Rev.* **2006**, *2*, 403–422. [CrossRef]
7. Way, S.A. High Performance Work Systems and Intermediate Indicators of Firm Performance Within the US Small Business Sector. *J. Manag.* **2002**, *28*, 765–785. [CrossRef]
8. Jebali, D.; Meschitti, V. HRM as a Catalyst for Innovation in Start-ups. *Empl. Relat.* **2021**, *43*, 555–570. [CrossRef]
9. Prieto-Pastor, I.; Martin-Perez, V. Does HRM Generate Ambidextrous Employees for Ambidextrous Learning? The Moderating Role of Management Support. *Int. J. Hum. Resour. Manag.* **2015**, *26*, 589–615. [CrossRef]
10. Pfeffer, J.; Veiga, J.F. Putting People First for Organizational Success. *IEEE Eng. Manag. Rev.* **1999**, *27*, 50–60. [CrossRef]
11. Lin, C.-H.; Sanders, K. HRM and Innovation: A Multi-level Organisational Learning Perspective. *Hum. Resour. Manag. J.* **2017**, *27*, 300–317. [CrossRef]
12. Polychroniou, P.V.; Giannikos, I. A Fuzzy Multicriteria Decision-Making Methodology for Selection of Human Resources in a Greek Private Bank. *Career Dev. Int.* **2009**, *14*, 372–387. [CrossRef]
13. Liang, G.S.; Wang, M.J.J. Personnel Selection Using Fuzzy MCDM Algorithm. *Eur. J. Oper. Res.* **1994**, *78*, 22–33. [CrossRef]
14. Hwang, C.-L.; Yoon, K. Methods for Multiple Attribute Decision Making. In *Multiple Attribute Decision Making: Methods and Applications a State-of-the-Art Survey*; Springer: Berlin/Heidelberg, Germany, 1981; pp. 58–191.
15. Wang, Z.; Yao, S.; Li, G.; Zhang, Q. Multiobjective Combinatorial Optimization Using a Single Deep Reinforcement Learning Model. *IEEE Trans. Cybern.* **2023**, 1–13. [CrossRef] [PubMed]
16. Leung, M.F.; Wang, J. A Collaborative Neurodynamic Approach to Multiobjective Optimization. *IEEE Trans. Neural Netw. Learn. Syst.* **2018**, *29*, 5738–5748. [CrossRef]
17. VakilZadeh, M.; Shayanfar, M.; Zabihi-Samani, M.; Ravanshadnia, M. Competency-Based Selection and Assignment for Project Manager in Iranian Railways Projects by Genetic Multigenic Programming. *Decis. Mak. Appl. Manag. Eng.* **2023**, *6*, 808–827. [CrossRef]
18. Dwivedi, P.; Chaturvedi, V.; Vashist, J.K. Efficient Team Formation from Pool of Talent: Comparing AHP-LP and TOPSIS-LP Approach. *J. Enterp. Inf. Manag.* **2020**, *33*, 1293–1318. [CrossRef]
19. Merigó, J.M.; Gil-Lafuente, A.M. Decision-Making in Sport Management Based on the OWA Operator. *Expert Syst. Appl.* **2011**, *38*, 10408–10413. [CrossRef]
20. Canós, L.; Casasús, T.; Liern, V.; Pérez, J.C. Soft Computing Methods for Personnel Selection Based on the Valuation of Competences. *Int. J. Intell. Syst.* **2014**, *29*, 1079–1099. [CrossRef]
21. Butler, J.E.; Ferris, G.R.; Napier, N. Strategy and Human Resource Management. *Ind. Labor Relat. Rev.* **1992**, *45*, 395. [CrossRef]
22. Canós, L.; Liern, V. Soft Computing-Based Aggregation Methods for Human Resource Management. *Eur. J. Oper. Res.* **2008**, *189*, 669–681. [CrossRef]
23. Filev, D.; Yager, R.R. On the Issue of Obtaining OWA Operator Weights. *Fuzzy Sets Syst.* **1998**, *94*, 157–169. [CrossRef]
24. Yager, R.R. Induced Aggregation Operators. *Fuzzy Sets Syst.* **2003**, *137*, 59–69. [CrossRef]
25. Yager, R.R. Generalized OWA Aggregation Operators. *Fuzzy Optim. Decis. Mak.* **2004**, *3*, 93–107. [CrossRef]
26. Muñoz, M.M.; Rojas-de-Gracia, M.-M.; Navas-Sarasola, C. Measuring Engagement on Twitter Using a Composite Index: An Application to Social Media Influencers. *J. Informetr.* **2022**, *16*, 101323. [CrossRef]
27. Acuña-Soto, C.; Liern, V.; Pérez-Gladish, B. Normalization in TOPSIS-Based Approaches with Data of Different Nature: Application to the Ranking of Mathematical Videos. *Ann. Oper. Res.* **2021**, *296*, 541–569. [CrossRef]
28. Liern, V.; Pérez-Gladish, B. Ranking Corporate Sustainability: A Flexible Multidimensional Approach Based on Linguistic Variables. *Int. Trans. Oper. Res.* **2018**, *25*, 1081–1100. [CrossRef]
29. Zhao, C.; Chen, J.; Yang, X.; Yuan, J. Social and Economic Impact Assessment of Coal Power Phase-Down at the Provincial Level: An Entropy-Based TOPSIS Approach. *Sustainability* **2023**, *15*, 16175. [CrossRef]
30. Yager, R.R. On Ordered Weighted Averaging Aggregation Operators in Multicriteria Decisionmaking. *IEEE Trans. Syst. Man Cybern.* **1988**, *18*, 183–190. [CrossRef]